Consumption context and personalization

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Abstract

The enormous offer of video content on the internet and TV broadcast networks requires new instruments to assist people with the selecting process. This overabundance of audio-visual material can be handled by a recommendation system that learns user preferences and helps people find interesting content. Present-day recommendation systems focus on the metadata or the consumption behaviour to select the content but take no additional contextual information into account. However, we conducted a user survey which showed that the consumption behaviour is strongly influenced by the context (location, time, etc). Therefore, we present in this paper a design for recommendation systems which incorporates this consumption context in order to improve the results.

2. Introduction

Nowadays, the offer of video content on the internet is abundant and is even still increasing. The web 2.0 video sites like YouTube[1] and Metacafe[2], are extremely popular. Recent initiatives like Joost[3] introduce a new way of watching television on the internet. In addition, the number of available TV channels has increased enormously by the introduction of digital television. These new ways of consuming video content augment the offer of the traditional genres. Besides, the range of the available genres is broadened by the introduction of theme channels like sports, fashion, cartoon, …

These new services complicated video retrieval for the end user who can only consume a small fractions of the overwhelming quantity of video content. Furthermore, a lot of videos are annoying, irrelevant or not in the field of interest of the user. Most video sites use a keyword based search tool to address these issues. Nevertheless, this rudimentary search tool is not capable to weed out irrelevant content. A second filtering based on user ratings or consumption behaviour can assist, but has a big dependency on the community itself.

The situation for digital TV is even worse. To find the most suited television programme, one has to thumb through a thick printed TV guide, or make an appeal to an Electronic Program Guide (EPG). However, most of these EPG's still lack intelligence and do not provide a personalized solution.

Recommendation systems try to solve this problem by creating and updating a user profile in the background and then filtering and recommending content according to the gathered preference information.

3. The content's metadata

Content can be described in different ways, each with their pro's and contra's. The content can be annotated by structured information that categorizes and describes it. Examples are MPEG7, TV-Anytime and RDF (Resource Description Framework). MPEG7 [7] describes its features by descriptors. The structure and the semantics of the relations between these descriptors are specified by description schemes. The description definition language is based on XML and allows the creation and modification of description schemes and the creation of new descriptors.

TV-Anytime, is a standard built on top of MPEG7. It was introduced by the TV-Anytime forum [4] and published by the European Telecommunications Standards Institute (ETSI)[5]. TV-Anytime uses the MPEG-7 description definition language to describe the metadata structure and XML for the encoding. This very structured classification practice is often referred to as “taxonomy'”.

RDF is a specification of the World Wide Web Consortium (W3C) designed to organize metadata [5]. The basic idea of RDF[6] is to add a meaning to the metadata by using the ”subject-predicate-object” representations. In this triple, the predicate expresses a relationship between the subject and the object. The RDF structure creates the possibility to link metadata of diverse information sources. Furthermore, Dublin Core can be used in RDF

[1] http://www.youtube.com
[2] http://www.metacafe.com
[3] http://www.joost.com
[4] http://www.tv-anytime.org
[5] http://www.etsi.org
[6] http://www.w3.org/RDF

descriptions. The Dublin Core is a set of predefined properties for describing documents [7].

On the web, where we witness the generation of a lot of user generated content, more practical approaches, like tagging, are common. A tag is a (relevant) keyword or term associated with or assigned to a piece of information. Such a metadata description is the contribution of the whole community. This social classification system, also known as “folksonomy” [10] has become very popular on the web around 2004. A disadvantage of folksonomy is that every user will tag in a different manner and use other synonyms [3].

4 Types of recommendation algorithms

From an algorithmic point of view, recommendation systems can be classified into three groups: rule-based, content-based and collaborative filtering systems. Rule-based filtering systems rely on manually or automatically generated decision rules to recommend items to users [8]. Like most rule-based systems, this type of filtering relies heavily on knowledge engineering by system designers to construct a rule base in accordance to the specific characteristics of the domain. The user profiles are generally obtained through explicit user interaction and are based on demographic or other personal characteristics of users. Many existing e-commerce Web sites utilize a rule-based filtering system.

Content based filtering systems create a user profile which captures the metadata of items in which that user has previously expressed interest [12]. To filter content, the recommendation system compares the extracted features from unseen of unrated items with the metadata in the user profile [11]. Content items which are sufficiently similar to the user profile are recommended to the user.

Collaborative filtering systems try to predict the user's appreciation for a content item by identifying similarities in the patterns of rating or consumption behaviour [9]. Therefore, this type of filtering is typically used when no (structured) metadata is available. Two types of collaborative filtering can be distinguished: item-based and user-based [4]. An item-based collaborative filtering system builds an item-item similarity matrix to identify related content items [6]. To predict the user's appreciation for a content item, the recommender relies on the behaviour, of that user, on similar items. An user-based collaborative filtering system compares patterns of behaviour in an user-user similarity matrix. The user's appreciation for a content item is predicted by the behaviour of the users who have a sufficiently similar profile.

From an architectural point of view, recommendation algorithms fall into two categories: memory-based and model-based. Memory-based algorithms are characterized by the fact that the learning is done online while the system is performing the personalization tasks. User based collaborative filtering and most content based filtering systems are examples of the memory-based approach. Model-based algorithms, on the other hand, utilize offline training data to learn models. Item-based collaborative filtering is a typical example of model-based learning.

5. The consumption context

To calculate the recommendations, traditional personalisation systems rely on a user profile that reflects the personal taste. We conducted a user survey to determine if there are other sources of influence in the content selection process, besides the personal taste.

Ten people (eight men and two women, all between twenty and thirty years old) were questioned about their viewing behaviour. They indicated in a checklist which of the proposed criteria had an effect on their content selection. The suggested criteria were: personal taste, user habit, popularity of the content, content quality, time, location, activity and mood of the user. Every person admitted that their viewing and content selection behaviour is not merely determined by their personal taste but is also influenced by at least one context feature.

The user survey indicated that the consumption context (location, time, etc.) made a significant difference on the content selection process. Therefore, we propose a recommendation system, where we store the consumption context as an extra information source (Figure 1). Including these extra context dimensions in the recommendation algorithm might improve its results [2].

The most important factor remains the user's personal taste, expressed by his/her profile. Related is the personal habit, which could improve the recommendation results. News, weather forecast and series are typically watched on a regular basis (e.g. every evening, every week). Moreover, TV-series can be truly addictive for viewers who are keen on watching the sequel. Consequently, those user habits are an important feature in the content selection procedure. Logging these habits creates the possibility to involve them in future recommendations.

Our survey confirmed that users are really fond of recent and popular content. The content items,

[7] http://dublincore.org/

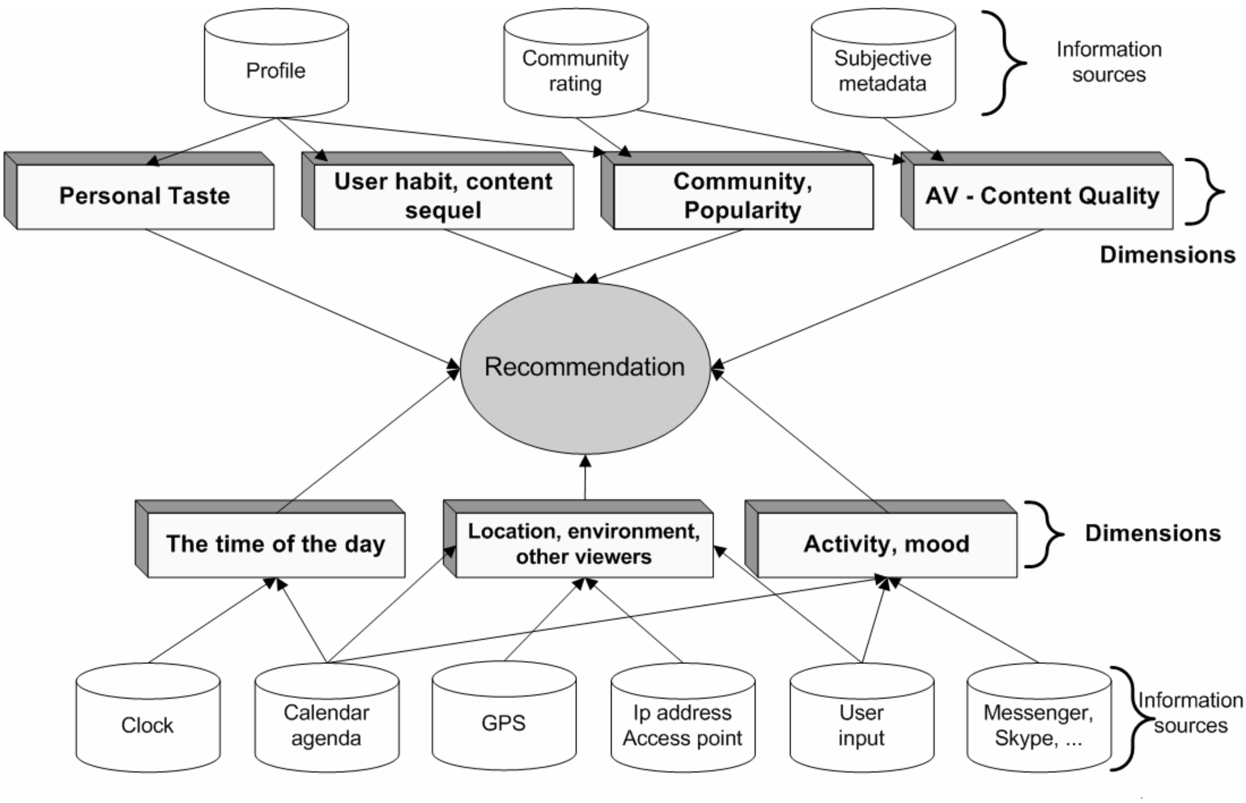

Figure 1: Extra context dimensions to involve in the recommendation process

which are viewed the most and get the best ratings by the community can be considered as the most popular. Sorting based on popularity, which is used on many video websites, is truly effective if no personalized ordering is available. Moreover, users can be clustered in smaller groups with different tastes. In this way, the popularity of content items can vary between the different clusters of users. Analyzing the behaviour of these individual clusters, might reveal more precise user expectations.

In general, metadata provides a very objective description of the audio-visual data but disregards the audio-visual quality, the sporting achievement, the acting performance, etc. Consequently, we believe that subjective metadata can assist in formulating recommendations. This subjective metadata could be delivered by the content provider or derived from community comments and behaviour.

Our user survey showed that the viewing behaviour changes during the day. In the morning, one does not want to watch movies but either daily news or the weather forecast [1]. In addition, the viewing habits in the weekend can differ from those during the week. Therefore, it is valuable to integrate a clock and a calendar in the recommendation system.

Since users consume content on a wide diversity of places, the location might have a significant influence on the recommendation process [2]. People like different content at work, on the train, at home, ... The user's position can be retrieved by his/her agenda, IP address, GPS or access point. The content preferences can vary with the audience as well: different content is consumed with friends, with family, alone, etc. Since it is not that evident to get information about the audience (e.g. to know who is before the television screen), users will have to specify this.

Last but not least is the activity and mood of the user. The survey showed that the mood (sad, cheerful, tired, ...) has a significant influence on the viewing preferences as well. The user activity (working, waiting for the train, relaxing, ...) is correlated with the user location and can be retrieved by user input or an instant messaging status.

6 Future work

Stimulated by the results of our user survey, we plan to implement a test framework for delivering video content, which takes the consumption context into account. Recommendation algorithms enhanced with the knowledge of these context dimensions will be bench-marked against algorithms without this context information. Furthermore, we will try to measure the influence of the proposed context dimensions and investigate the potential effect of additional consumption information.

7. Conclusion

Because of the overabundance of content on the internet and digital television, personalisation becomes a necessity to help users with the content selection process. A wide diversity of personalisation techniques already exists. However, traditional recommendation algorithms ignore the consumption context. We conducted a user survey that proved the influence of this consumption context on the viewing and content selection behaviour. Therefore, we proposed a design in which the recommendation engine disposes of extra information, besides the personal taste. These extra influence factors are: user habit, popularity of the content, content quality, time, location, activity and mood of the user.

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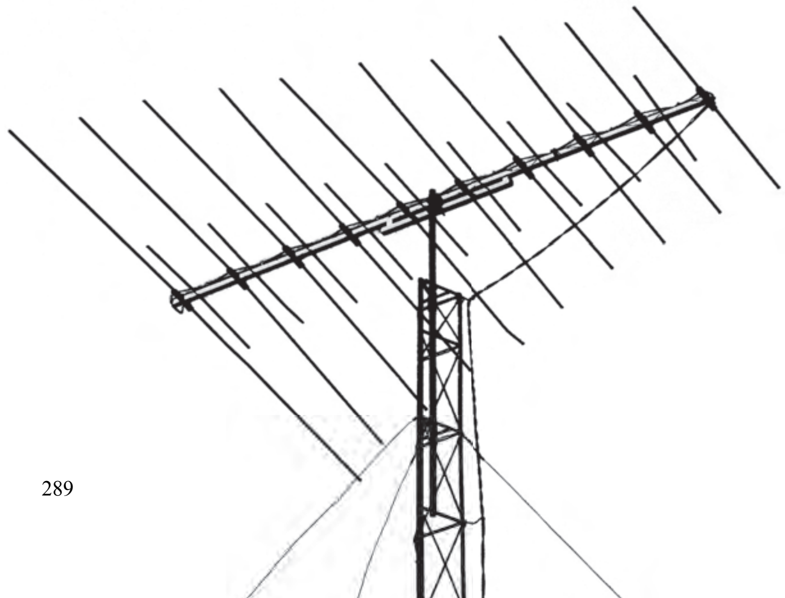

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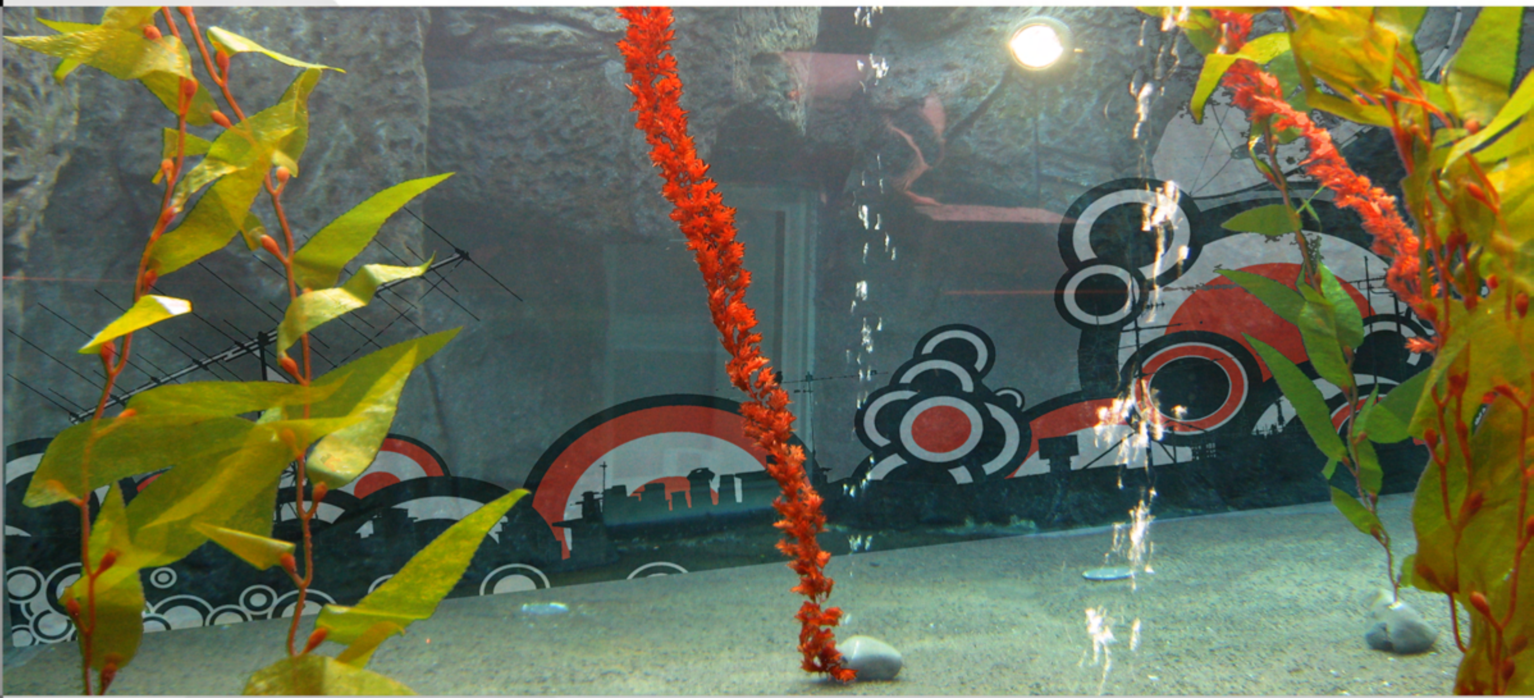

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